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Error in the Real-Time Identification of Breaks

NUR-SYAZWANI, M.[a*] AND BULKLEY, G.[b]

[a]*Faculty of Economics and Management, Universiti Putra Malaysia, Malaysia*
[b]*School of Economics, University of Bristol, United Kingdom*

ABSTRACT

We studied the mistakes that happen in the real-time identification of structural breaks in the selected aggregate-level of U.S. financial data series. We were interested in the real-time identification because of its relevance for forecasting. The level of the noisiness of different datasets and techniques used for the identification of breaks affected the frequency of the mistakes encountered in real-time. We found that mistakes in not finding the true breaks and/or finding the wrong ones in real-time were made more frequently in the case of a noisier financial dataset. Moreover, the techniques for optimal break detection based on the sequential learning of Bai and Perron (2003) were found to make fewer mistakes than those based on the Information Criteria (IC).

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[*]Corresponding author: Email: nur.syazwani@upm.edu.my

INTRODUCTION

Many economic and financial time series are subject to structural breaks or changes as a result of changes in tastes, technology or policy. The presence of breaks in time series is widely recognised, if ignored, they may lead to serious implications. It is, therefore, a crucial matter, that needs to be dealt with using special care and attention, or otherwise one may obtain spurious results as argued by Perron (1989). Moreover, breaks can pose a serious problem for forecasting. Pástor and Stambaugh (2012) also argued that "estimation risk" is one of the key components of long-horizon forecasting uncertainty.

Pástor and Stambaugh (2012) argued that "estimation risk" is one of the key components of long-horizon forecasting uncertainty. There is a large amount of prior literature on the development of techniques for identifying breaks in a given dataset (e.g. Alogoskoufis and Smith (1991); Stock and Watson (1996); Pesaran and Timmermann (2002); Stock and Watson (2003); Rapach and Wohar (2006); Breitung and Eickmeier (2011)). Some recent literature has focused on developing approaches for forecasting under the presence of breaks.[1] Rossi et al. (2012) reviewed the empirical analyses that have been carried out on the advances in forecasting under the presence of breaks. A key question is what dataset to employ to estimate the parameters of the forecasting model. Since forecasts are typically based on the assumption of the constancy of the model parameters, the potential for breaks implies that a key forecasting problem is to determine which dataset to employ to estimate the parameters of the model that will generate future observations. This requires judging if and when there has been a break in the past data. If there is judged to have been a recent break then there is a further question of whether the model should be solely estimated on the post-break data or whether there is any incremental information in the pre-break data.

In this paper, we considered another aspect of the problem of forecasting in an environment where there are uncertain break dates. We studied the problem of learning about break dates and examined the dynamics of how agents learn about the occurrence of breaks in real-time. Intuitively, the problem for an agent in real-time is judging whether an extreme observation is just an outlier from an unchanged structural model, or whether it is the first observation from a model with revised parameters. We investigated how often different techniques mistakenly identified breaks in real-time when we knew with hindsight from the full dataset that no break had occurred.

The liquidity crisis that arose in 2008 offers an example of this problem. The crisis was so severe that at times confidence was eroded to the point that it was considered just another shock that was drawn from the same distribution of shocks over the previous 50 years. Many commentators argued that the future might resemble a 1930s style depression or the low growth environment observed in Japan since the early 1990s. This would be an example of a potential structural break in the economy. Confidence has gradually returned that this was not a structural break but rather a very extreme observation in a given model. However, at the time of writing, there were still different views on this point. As more data accumulate, the apparent break turns out merely to have been a few extreme observations in an unchanged model. The nearly halving of stock prices in 2008 can only reflect the opinion of many investors that a structural break had occurred in 2008. The recovery of stock markets from that low point can be interpreted in the context of the ideas of this study as the result of a gradual revival of confidence that a permanent break had not occurred.

In our previous paper, Nur-Syazwani and Bulkley (2015), we provided the empirical evidence of the instability in the firm-level dividend of U.S. firms. In this paper, we obtained the aggregate-level financial data series i.e. dividends, earnings and prices from Shiller (2013). Following Timmermann (2001), we modelled the growth processes in dividends and the same for earnings and prices as well. The key results from our study of the real-time dynamics of breaks are summarised below:

The breaks found, with the benefit of hindsight, were found to be linked to some major or significant events in economic and financial history. This provides us with good grounds to assume that these breaks are the true breaks in our study.

In real-time, it is more likely for mistakes to be made in the case of a noisier dataset, or a dataset with higher volatility.

[1]Some of the papers on the topic of forecasting in the presence of breaks are by Stock and Watson (2003), Pesaran and Timmermann (2002) and Giacomini and Rossi (2009), Groen *et al.* (2013), Pesaran *et al.* (2013) etc.

For the four techniques for optimal break detection from Bai and Perron (2003), the Bayesian Information Criterion (BIC) reports the highest number of total false breaks found compared to the other techniques for optimal break selection; Sequential, Repartition and the modified version of Schwarz' criterion proposed by Liu et al. (1997) and abbreviated as LWZ.

It is important to identify any error or mistake that can potentially be made in the identification of breaks. In real-time, we have limited information and this may further limit the ability of any methodology used for the detection of breaks. As we obtain more data, the results may also change accordingly. This will affect the accuracy of economic and financial forecasting and the decisions made based on the forecasts can be misleading. In a practical sense, a misleading decision can be very costly if required to be reversed and/or rectified. Therefore, the realisation of any potential error that can be made in break identification is crucial to ensure that good quality forecasts are produced. This paper serves to examine this issue in more detail.
The techniques for break identification used in this paper are based on Bai and Perron (2003). In a technical sense, we believe that selecting simple (linear) but yet highly reliable techniques for break identification can help illustrate how the error can be identified in real-time more efficiently. This is done by applying the technique of real-time analysis of Clements and Galvão (2013). In this paper, we combined the two methods of linear break identification and real-time analysis of Bai and Perron (2003) and Clements and Galvão (2013) to study any error or mistake in the real-time identification of breaks. Prior literature has seen a growing number of studies that have emphasised the importance of considering the non-linear nature of most financial data series and hence suggesting that techniques based on non-linearity are more appropriate for that matter. On the contrary, prior literature also highlights that the increasing complexity of the methodology used does not necessarily translate into greater accuracy. A comparison made by Stock and Watson (1998) between linear and nonlinear univariate models for forecasting macroeconomic time series showed a preference towards simpler linear models, which were argued to give the overall best forecasting performance.

DATA AND METHODOLOGY

Aggregate-level data

The monthly data on the dividend, earnings and price series, denoted by D_t, E_t and P_t for the time period that begins from January 1871 until December 2013 were obtained from continuously updated-data following Shiller (2013). The computation of 'Online Data Robert Shiller' on monthly dividend and earnings is from the S&P four-quarter totals for the quarter since 1926, with linear interpolation to monthly figures. The data on dividend and earnings before 1926 were compiled from Cowles (1939), with linear interpolation from the annual figures. Moreover, the monthly data on stock prices were computed from averaging the daily closing prices and the data on the CPI (Consumer Price Index-All Urban Consumers) starting from 1913 and were obtained from the U.S. Bureau of Labor Statistics. For the years before 1913, the data on the CPI was extracted from the CPI Warren and Pearson's price index (Warren and Pearson (2017)).
The aggregate-level financial series considered in this paper differed in terms of their level of noisiness. Figure 1 plots the aggregate real-dividend, earnings and price from 1871-2013 obtained from Shiller (2013). The processes related to aggregate-level prices were seen to be noisier than the processes related to aggregate-level earnings. The processes related to aggregate-level dividends were the least noisy compared to the rest. Hence, it was possible to see how the level of noisiness in a dataset can affect the real-time dynamics of breaks.

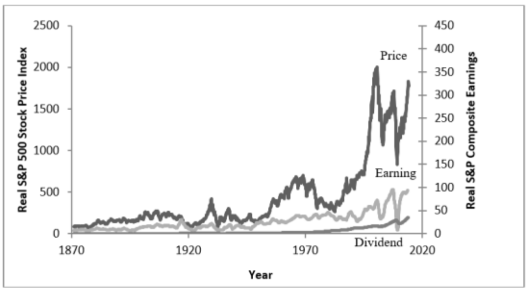

Figure 1 Plots for the Aggregate Real Dividend, Earnings and Price from 1871-2013
(Source: 'Online Data Robert Shiller' http://www.econ.yale.edu/~shiller/data.htm)

We converted the series of the dividend, earnings and price into real dividends, earnings and price by using the Consumer Price Index (CPI) obtained from the same source as well. The left-hand side or dependent variable in our structural break analysis in real-time was the growth rate of the real dividends, prices and earnings. Thus, we modelled the change in the logarithm of the real dividend, earnings and price as follows:

$d_t = \Delta \log (D_t)$
$e_t = \Delta \log (E_t)$
$p_t = \Delta \log (P_t)$

Furthermore, we also considered the absolute value of the growth rate i.e. $|d_t|$, $|e_t|$ and $|p_t|$ in the above aggregate-level financial series which allowed us to detect possible breaks in the volatility of the processes related to the above aggregate-level financial series.

Structural break analysis

We utilised the Bai and Perron (2003) program that allowed for the construction of estimates of the parameters in models with multiple structural breaks. The algorithm of this program is based on the principle of dynamic programming and information criteria and sequential hypothesis testing to give the optimal number of breaks. Besides that, it was also designed to construct confidence intervals and test for structural change. We can also estimate either pure or partial structural change models and choose the options whether to allow for heterogeneity and/or serial correlation in the data and the errors across segments or not.

The multiple linear regression models with m breaks (m+1 regimes) are described as follows:

$$\begin{aligned} y_t &= x_t'\beta + z_t'\delta_1 + u_t, \qquad & t &= 1, \dots, T_1 \\ y_t &= x_t'\beta + z_t'\delta_2 + u_t, \qquad & t &= T_1 + 1, \dots, T_2 \\ &\vdots \\ y_t &= x_t'\beta + z_t'\delta_{m+1} + u_t, \qquad & t &= T_{m+1} + 1, \dots, T \end{aligned} \tag{1}$$

Where y_t is the observed dependent or response variable at time t; x_t(p x 1) is the vector of variable(s), fixed throughout the analysis; z_t(q x 1) is the vector of variable(s) subject to structural breaks at time t, β and δ_j(j = 1,...,m+1) are the vectors of coefficients of x_t and z_t respectively; u_t is the error or disturbance at time t. The maximum number of breakpoints is given by m.

For the purpose of our structural break analysis, we considered two different (general) structural break models as follows:

Trend-stationary break model (Model 1):

$$y_t = \alpha + \beta t + u_t \tag{2}$$

Where t is time, f is a deterministic (linear) function, in which f(t)= and u_t is the disturbance at time t. The variable(s) subject to breaks is given by z_t={α , t} whereas x_t={}.

Autoregressive break model (Model 2):

$$y_t = \alpha + \beta\, y_{t-1} + u_t \tag{3}$$

Where t is time, α is drift, y_{t-1} is the lag of dependent variable or unit root term and ut is the disturbance at time t. The variable(s) subject to breaks is given by z_t={α, y_{t-1}} whereas x_t={}.

Real-time analysis

In general, following Clements and Galvão (2013), we had access to the "vintage" T values of the observations on y up to time period T-1, where "vintage" is defined as the information set that one has available in hand at a given or specific date and the compilation of such vintage is the "real-time dataset" (Croushore and Stark 2003). The T-vintage can be written as $\{y_t^T\}$t=1,2,…T-1. This is also called the latest available T-vintage, whereas the previous vintages, for example, the T-j vintage is $\{y_t^{T-j}\}$ for j=1,2,3,…, and where t=1,2,…,T-j-1. When we have the full dataset with hindsight, we have the T-vintage in which the true breaks are detected by using the full dataset. The regression model for T-vintage with m breaks (m+1 regimes) of interest is

$$\begin{aligned}
y_t^T &= x_t'^T\beta + z_t'^T\delta_1 + e_t^T, && t = 1,\dots,T_1\\
y_t^T &= x_t'^T\beta + z_t'^T\delta_2 + e_t^T, && t = T_1+1,\dots,T_2\\
&\vdots\\
y_t^T &= x_t'^T\beta + z_t'^T\delta_{m+1} + e_t^T, && t = T_{m+1}+1,\dots,T\text{-}1 \qquad (4)
\end{aligned}$$

The true set of breaks is given by $\{T_k\}$ where k=1,2,…,m where m is the maximum number of breaks allowed in the empirical exercise.

For the real-time analysis, we carried out the structural breaks analysis of the Bai and Perron (2003) program by using all the previous vintages that we had, i.e. $\{y_t^{T-j}\}$ for j=1,2,3,…, and where t=1,2,…,T-j-1.

$$\begin{aligned}
y_t^{T-j} &= x_t'^{T-j}\beta + z_t'^{T-j}\delta_1 + e_t^{T-j}, && t = 1,\dots,T_1\\
y_t^{T-j} &= x_t'^{T-j}\beta + z_t'^{T-j}\delta_2 + e_t^{T-j}, && t = T_1+1,\dots,T_2\\
&\vdots\\
y_t^{T-j} &= x_t'^{T-j}\beta + z_t'^{T-j}\delta_{m+1} + e_t^{T-j}, && t = T_{m+1}+1,\dots,T\text{-j-}1 \qquad (5)
\end{aligned}$$

With the benefit of hindsight that a break had occurred at the 5% significance level, we would expect to find the same break as more data arrived. For instance, we would expect to detect a break at a past date i.e. $\{y_t^T\}$, where t=1,2,…T-1. Similarly, we would always expect to detect the same break in the next periods as more data become available.

However, there are times when this may not be the case. The error in judgement in real-time may be present in the form of Type 1 and Type 2 errors:

Type 1 error: This happens in the case of a rejection of the null hypothesis of no break when it is actually true i.e. a break was identified when there was no break.
Type 2 error: This happens in the case of a failure to reject the null hypothesis when it is actually not true i.e. a break was not identified when there was a break.

In the context of our structural break analysis in real-time, if we were to explain a judgement error in terms of either a Type 1 or Type 2 error, as it would naturally have been thought of, this would lead us to some confusion, which could further lead to a misleading analysis.

To analyse the mistakes in the detection of structural breaks in real-time, the following would have been our set of hypotheses:

Null hypothesis: There is no (true) break(s) at data point t
Alternative hypothesis: There is a (true) break(s) at data point t

Essentially, we investigated the following:

How often do we find or not find the wrong or true break(s) given the different levels of the noisiness of the dataset in real-time respectively?

RESULTS

Structural breaks in the aggregate-level series in hindsight

The Bai and Perron (2003) method involve extensive programming that allows the construction of the estimates of parameters in models with multiple structural changes (the main essence is a dynamic programming algorithm). By setting m=8, the maximum number of breaks allowed is 8 and by treating the number of breaks as known, the Global Optimization procedure estimates the break dates for m=1, 2, 3, 4, 5, 6, 7, 8. The optimal number of breaks is estimated by using the Information Criteria (BIC and LWZ), Sequential and Repartition test. Timmermann (2001) tested the breaks in the endowment process by using the Gauss program provided by Bai and Perron (1998). The maximum number of breakpoints is set to 8 as well, and by allowing the

heteroscedasticity in the residuals; he presented the evidence of structural breaks in the U.S. dividend series. He utilised monthly data on dividends from 1871-1999 obtained from Shiller (2000). Dividends were converted into the real dividends by, D_t. The dependent or left-hand side variable is the change in the logarithm of D_t, i.e. the real dividend growth rate, $d_t = \Delta \log (Dt)$.
Timmermann (2001)presented the results of the following processes:

Dividend growth
Absolute dividend growth
Dividend growth with lag
Absolute dividend growth with lag

The same processes were included in our investigation together with some other processes of the aggregate-level time series of earnings and price as well. We demonstrated the results by applying different specifications in two different models. The first model was based on the univariate specifications with a drift or an intercept term as the regressor was subjected to structural breaks whereas the second model included drift or the intercept term and a single lag of the dependent variable as the regressors were subjected to structural breaks.
Table 1 presents the estimated number of optimal breakpoints by the techniques for optimal break selection for all of the processes for the two models. The estimated number of breakpoints, by using the Bai and Perron (2003) method, which is the modified version of the Bai and Perron (1998) method applied by Timmermann (2001) for the above four processes are consistent with Timmermann (2001). The Sequential and Repartition breakpoint tests used a significance level of 5%, while the two information criteria, the BIC and LWZ were based on the penalised likelihood function. The Sequential and Repartition tests failed to detect any break for most of the processes when there was only an intercept term included as the regressor but by including a single lag as another regressor, the estimated number of breakpoints reported by the Sequential and Repartition tests was higher when compared to the BIC technique. The LWZ method was observed to be more stringent and the estimated number of breaks was always lower than the BIC technique.

Table 1 The Estimated Number of Breakpoints, Bai and Perron (2003) Method

Process	Sequential	Repartition	BIC	LWZ
Model 1: Stationary Break Model				
Abs. dividend growth*	2	2	5	1
Abs. earnings growth	0	0	5	1
Abs. price growth	3	3	2	2
Dividend growth*	0	0	4	0
Earnings growth	0	0	0	0
Price growth	0	0	0	0
Model 2: Autoregressive Break Model				
Abs. dividend growth with lag*	6	6	4	1
Abs. earnings growth with lag	0	0	2	1
Abs. price growth with lag	3	3	2	2
Dividend growth with lag*	3	3	1	1
Earnings growth with lag	5	5	1	1
Price growth with lag	0	0	0	0

Note: * The number of breakpoints matched those reported by Timmermann (2001) and any additional breakpoint(s) found here is outside the time period considered by Timmermann (2001).

Error in Real-Time

Table 2 presents the descriptive statistics of the number of dates where we did not find an earlier true break in real-time. We observed that for the absolute growth processes, the noisier a dataset is, the more dates we did not find a break at a date where there was indeed a true break. In terms of the comparison between the techniques for break detection, it is interesting to see that for the processes related to growth in the dividend, the BIC found the highest number of dates where we did not find the true breaks followed by the LWZ, and Sequential and Repartition for the processes related to growth in the dividend. However, for the processes related to growth in price, this was not the case. Overall, the autoregressive model (Model 2) reported, mostly, a higher number of dates at which the true breaks were not found compared to the stationary break model (Model 1).

Table 2: Error in the Identification of Breaks in Real-Time, Bai and Perron (2003) Program

Procedure	Process	Descriptive Statistics						
		Model 1: Stationary Break Model						
		N	**Mean**	**Median**	**Std. Dev.**	**Min**	**Max**	**Range**
Sequential	Absolute dividend growth	2	80	80	N/A	N/A	N/A	N/A
	Absolute price growth	3	304	307	263.51	39	566	527
Repartition	Absolute dividend growth	2	80	80	N/A	N/A	N/A	N/A
	Absolute price growth	3	523.33	692	353.58	117	761	644
BIC	Absolute dividend growth	5	233.25	132	277.59	27	642	615
	Absolute earnings growth	5	330.75	336.50	199.34	109	541	432
	Absolute price growth	2	371.50	371.50	297.69	161	582	421
	Dividend growth	4	613.25	628.50	92.96	492	704	212
LWZ	Absolute dividend growth	1	198	198	N/A	N/A	N/A	N/A
	Absolute price growth	2	428.50	428.50	350.02	181	676	495
		Model 2: Autoregressive Break Model						
Sequential	Absolute dividend growth	6	472.40	540	361.51	42	980	938
	Absolute price growth	3	764.67	1005	424.09	275	1014	739
	Dividend growth	3	591.67	267	590.92	167	1540	1373
	Earnings growth	5	763.60	636	335.26	511	1144	633
Repartition	Absolute dividend growth	6	417.40	248	369.16	42	980	938
	Absolute price growth	3	499	691	397.45	42	764	722
	Dividend growth	3	247.67	286	189.43	42	415	373
	Earnings growth	5	474	212	533.65	3	1215	1212
BIC	Absolute dividend growth	4	361.50	361.50	54.45	323	400	77
	Absolute earnings growth	2	812	812	216.37	659	965	306
	Absolute price growth	2	985	1135	518.53	251	1418	1167
	Dividend growth	1	671	671	N/A	N/A	N/A	N/A
	Earnings growth	1	1139	1139	N/A	N/A	N/A	N/A
LWZ	Absolute dividend growth	1	497	497	N/A	N/A	N/A	N/A
	Absolute price growth	2	399.50	399.50	54.45	361	438	77
	Dividend growth	1	905	905	N/A	N/A	N/A	N/A
	Earnings growth	1	1139	1139	N/A	N/A	N/A	N/A

An error can also happen when we found a break at a past date where there was no true break at that date in real-time. Table 3, on the other hand, presents the descriptive statistics of the number of dates where we did not find a break at a past date where there was no true break at that date in real-time i.e. we correctly did not find the wrong breaks. The BIC reported the highest number of total false breaks found compared to the other techniques for optimal break selection. Comparing the two break models, the autoregressive model (Model 2) reported a lower number of dates at which the false breaks were not found this was especially noted for Sequential and Repartition techniques but the evidence was not conclusive for the BIC and LWZ methods.

Table 3 Correct Identification of Breaks in Real-Time, Bai and Perron (2003) Program

Procedure	Process	Descriptive Statistics						
		Model 1: Stationary Break Model						
		N	**Mean**	**Median**	**Std. Dev.**	**Min**	**Max**	**Range**
Sequential	Absolute dividend growth	29	1333.69	1372	390.45	162	1705	1543
	Absolute price growth	36	1076.53	1017.50	486.44	263	1713	1450
Repartition	Absolute dividend growth	28	1426.29	1628	321.38	795	1708	913
	Absolute price growth	90	1058.07	1014	451.57	263	1713	1450
BIC	Absolute dividend growth	98	1201.80	1030.50	323.48	528	1709	1181
	Absolute earnings growth	179	1111.71	1052	424.87	123	1713	1590
	Absolute price growth	70	909.13	1088	528.26	86	1710	1624
	Dividend growth	112	1180.46	1110	299.36	739	1712	973
LWZ	Absolute dividend growth	20	1316.45	1636	424.24	779	1712	933
	Absolute price growth	34	1168.76	1016.50	350.24	760	1708	948
		Model 2: Autoregressive Break Model						
Sequential	Absolute dividend growth	29	1223.48	1219	493.41	201	1712	1511
	Absolute price growth	17	1001.12	945	571.18	42	1694	1652
	Dividend growth	28	1171.89	1155	422.80	42	1694	1652
	Earnings growth	72	36.80	17	128.84	1	754	753
Repartition	Absolute dividend growth	23	1143.65	1148	497.61	201	1711	1510
	Absolute price growth	27	1028.30	941	399.72	260	1694	1434
	Dividend growth	28	1227.18	1155	297.83	511	1694	1183
	Earnings growth	92	47.43	20	132.44	1	861	860

Table 3 Cont.

BIC	Absolute dividend growth	7	1528.57	1659	212.95	1035	1694	659
	Absolute earnings growth	16	1300.44	1216	323.99	829	1637	808
	Absolute price growth	23	1293.13	1193.50	171.10	1122	1646	524
	Dividend growth	0	N/A	N/A	N/A	N/A	N/A	N/A
	Earnings growth	4	1594.25	1640.5	102.13	1442	1654	212
LWZ	Absolute dividend growth	2	1366	1366	384.6661	1094	1638	544
	Absolute price growth	1	1323	1323	N/A	N/A	N/A	N/A
	Dividend growth	0	N/A	N/A	N/A	N/A	N/A	N/A
	Earnings growth	4	1594.25	1640.50	102.13	1442	1654	212

CONCLUSION

We were particularly concerned with the effect that breaks can pose for forecasting. Such concern has led many researchers to take the wise step of incorporating breaks in their forecasting models with the hope of generating more accurate and reliable forecasts. Our study focused more on exploring the topic of structural breaks where we looked at the dynamics of learning about breaks in real-time.

It is important to look at breaks from the real-time perspective as this captures what could actually have been attained with the data that is available at the present time. As more data become available, the view also changes accordingly. As previously mentioned, we could relate this to the recent financial crisis that arose in 2008. This would be a potential structural break in the economy. However, the techniques for optimal break selection considered in this paper did not find a break during this crisis. We offer an explanation of this situation from our point of view based on real-time learning about the dynamics of breaks. The availability of more data in subsequent periods may reveal that some apparent breaks turn out merely to have been a few extreme observations in an unchanged model.

In this paper, the breaks found in hindsight are assumed to be the true breaks for the purpose of real-time analysis. We observed links between these breaks and some major or significant events in history. We found that in real-time, it is more likely for mistakes to happen in the case of a noisier dataset. The Bayesian Information Criterion (BIC) was observed to record the highest number of total incorrectly identified breaks when compared to the other techniques for optimal break selection; Sequential, Repartition and the modified version of Schwarz' criterion proposed by Liu et al. (1997) abbreviated as LWZ.

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